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Classification of Fatty and Cirrhosis Liver Using Wavelet-Based Statistical Texture Features and Neural Network Classifier*

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Abstract Computational methods are useful for medical diagnosis because they provide additional information that cannot be obtained by simple visual interpretation. As a result an enormous amount of computer vision research effort has been targeted at achieving automated medical image analysis. The study and development of Probabilistic Neural Network (PNN), Linear Vector Quantization (LVQ) Neural Network and Back Propagation Neural Network (BPN) for classification of fatty and cirrhosis liver from Computerized Tomography (CT) abdominal images is reported in this work. Neural networks are supported by more conventional image processing operations in order to achieve the objective set. To evaluate the classifiers, Receiver Operating Characteristic (ROC) analysis is done and the results are also evaluated by the radiologists. Experimental results show that PNN is a good classifier, giving an accuracy of 95% by holdout method and giving an accuracy of 96% by 10 fold cross validation method for classifying fatty and cirrhosis liver using wavelet based statistical texture features.

Key words: probabilistic neural network; linear vector quatization neural network; back propagation neural network; biorthogonal wavelet transform; simple genetic algorithm; medical diagnosis

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1 Introduction

Visual interpretations of medical images are used for the early detection and diagnosis of diseases. The decision based on visual interpretations depends on the ability of the physicians to distinguish certain patterns or shape of the image. Diagnostic accuracy can be improved by providing additional information, generated by computational methods that cannot be obtained by simple visual interpretations. As a result, Computer Aided Diagnosis (CAD) has become one of the major research subjects in medical imaging and diagnostic radiology.

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In this work, the study and development of Probabilistic Neural Network (PNN), Linear Vector Quantization (LVQ) Neural Network and Back Propagation Neural Network (BPN) for classification of fatty and cirrhosis liver from Computerized Tomography (CT) abdominal images is reported. Neural networks are chosen for recognizing diseases from the features extracted from the liver images as there is no need to provide a specific explicit technique on how to identify the diseases. The neurons and networks supposed to learn from examples and store this knowledge in a distributed way among the connection weights for recognizing diseases. Preprocessing of liver images, the region of interest identification, segmentation, feature extraction and feature selection are done using image processing techniques.

2 Literature Survey

Organ segmentation is often the first step in computer aided diagnosis. Segmentation of abdominal organs such as the liver, kidneys and spleen from CT scan images has been attracting a fair amount of research recently. Many artifacts can arise in CT scans, among these are beam-hardening artifacts, which are noticeable as focal areas of low attenuation adjacent to bones, partial volume artifacts resulting from spatial averaging of disparatic tissues in close proximity and resulting in blurred edges and streak artifacts, the result of peristalsis, respiratory, cardiac and patient motion[24].

So far, the various approaches used for segmentation are histogram analyzer, gray level threshold, region growing, edge detection techniques, neural network based methods, texture transforms, mathematical morphology operations and pixel classification methods. Lee and Chung[5] used a segmentation method that is based on shape analysis, image contextual constraint and between slice relationships. J.E. Koss *et al.*[17] perform segmentation by exploiting small variations in textures of the soft tissue. The results achieved were quite poor. The major fault lies in the fact that organs have substructures that have different textures, as well as the fact that texture is not well defined. It is envisioned that this is the first step to automate segmentation. But the texture based segmentation result in a coarse and block wise contour, leading to poor boundary accuracy.

Chien Chang Lee *et al.*[4] proposed a method combining a multi module contextual neural network and spatial fuzzy rules and fuzzy descriptors for automatically identifying abdominal organs from a series of CT image slices. Ninety Nine percent of organ regions in the test images are correctly identified as its belonging organ, implying the high promise of the proposed method. However, training needs a large data set. In general, artificial neural networks designed for segmentation have many drawbacks. One of these is requirement of a large training set; another being that even if successful, it is unknown how to improve the network due to its opacity. K.T. Bal *et al.*[3] propose a method that uses some a priori information about organ morphology and digital image processing techniques. Extracted boundaries of the liver are smoothed using mathematical morphology techniques and B-splines. K.R. Hoffmann *et al.*[12] investigated the automatic extraction of the liver. However, about fifty percent of the data needed manual correction after being extracted. They used region growing technique based on the intensity. They studied the segmentation of hepatic vessels and metastates excluding the recognition of a disease. Rule based recognition of abdominal organs is a step that generally follows segmentation. Conceptually, it

is based on exploiting organ invariants. Unfortunately, with CT scans of abdominal organs, there are few invariants. Kobashi and Shapiro[15] have used eight different characteristics as classification criteria. This approach is very algorithmic and produces moderately good results. Among these techniques for segmentation, gray level threshold based on histogram analyzer followed by morphological operations are giving promising results. Much work has been done, but more work is necessary until the abdominal organ segmentation problem can be considered largely solved.

It is difficult to classify human body organ tissues using shape or gray level because the shape of each organ is not consistent throughout all 2D slices of a medical image and the gray level intensities overlap considerably over soft tissues. However, tissues are expected to have consistent and homogeneous structures, described as texture, within liver images makes use of image texture analysis suitable for computer assisted characterization. The most commonly used texture features that have been applied successfully to real world textures are the Spatial Gray Level Dependence Matrix (SGLDM)[10], Gray Level Run Length Statistics[9,26], Gray Level Difference (GLD) statistics[25], Laws Texture Energy Measures[20] and Fractal features[23]. A weakness shared by these texture analysis schemes is that the image is analyzed at one single scale, a limitation that can be lifted by employing multi scale representations. In a nutshell, S.G. Mallet[21] identified the important concept of multiresolution analysis which is the corner stone of modern wavelet theory, while I. Daubechies[6] constructed the first orthogonal wavelet bases that were compactly supported.

Yasser M. Kadah *et al.*[27] extracted the first order gray level parameters like mean and first percentile of the gray level distribution and second order gray level parameters like contrast, angular second moment, entropy and correlation and trained the functional neural network for automatic diagnosis of diffused liver diseases like fatty and cirrhosis using ultrasonic liver images and showed that very good diagnostic rates can be obtained using unconventional classifiers trained on actual patient data. Aleksandra Mojsilovic *et al.*[1] investigated the application and advantages of the non separable quincunx wavelet transform and used energies of the transformed regions to characterize liver tissues using ultrasonic liver images. A comparison between the quincunx and the traditional wavelet decomposition suggests that the quincunx transform is more appropriate for characterization of noisy data. Also, they compared with other texture measures like SGLDM, Fourier measures and Fractal texture measures. The classification accuracy was 87 percent for the SGLDM, 82 percent for the Fourier measures, 69 percent for Fractal measures and 90 percent for wavelet approach indicating the superiority of the wavelet approach.

Militiades Gletsos *et al.*[22] presented a system with two basic modules: the feature extraction module and classifier module. In their work, Region of Interest (ROI) were extracted manually by the experienced radiologist from CT images of normal liver, hepatic cysts, hemangiomas and hepato cellular carcinomas and fed to the feature extraction module. Extracted features were fed to the three hierarchially placed feed forward neural network. In their work, liver and suspicious region were extracted manually. This needs human intervention.

Yu-Len Huang *et al.*[28] manually selected the suspicious tumor region in the digitized CT image, extracted autocovariance texture features of subimage and identified the tumor as benign or malignant using support vector machine classifier. Kunishige

Matake *et al.*[18] showed that the artificial neural network can provide useful output which can be used as a second opinion to improve radiologist diagnostic performance in the differential diagnosis of hepatic masses seen on a contrast enhanced CT.

Literature survey shows that identifying abdominal organs from CT abdominal images is one of the essential steps in visualizing organ structure to assist in diagnosis. Texture analysis techniques for liver tissue characterization have been used in the past with very promising results. Wavelet approach enables us to analyze the image in multi scale representation. Texture classification experiments have been performed by Aleksandra Mojsilovic *et al.*[2] using Haar filters, Daubechies filters and eight different biorthogonal filter pairs. They reported that biorthogonal filters are more suitable for texture analysis.

In this work, the liver region is extracted by using the anatomic knowledge of the liver, adaptive threshold decision based on histogram analyzer and morphological operations from CT abdominal images. Then biorthogonal wavelet based statistical texture features are extracted from the liver region. The extracted features are optimized by Sequential Forward Floating Search (SFFS) and Genetic Algorithm[18, 14]. Optimized features are fed to the neural network classifier to classify the disease as fatty or cirrhosis liver.

3 Methodology

The data used in this work were collected from Devaki MRI & CT Scans, Madurai. The area of interest of the CT abdominal images was captured by SOMATOM Emotion Duo CT Scanner. Plain spiral CT scanning of liver was scanned from the right dome of diaphragm to just below the inferior border of the liver using 8 mm slices at 8 mm interval with 0 mm inter slice gap. 70 mAs technique was used with 110 KVP, field of Vision (foV) of 280 and image matrix of 256 x 256. 100 to 120 cc omnipaque 350 was injected intravenously at the rate of 3 cc per second and post contrast spiral CT scanning was done with 8 mm slices at 8 mm interval and 0 mm inter slice gap.

3.1 Liver extraction from CT abdominal image

CT abdominal image contains the images of the liver and other organs like spleen and stomach. Normally, the liver region is located in the upper left side of the abdomen and takes up the largest area among the various organs included in the image and the liver image maintains a constant intensity throughout. But a fixed threshold is not possible to extract liver region because, the intensity differs according to the patient, slice and the CT machine. Therefore adaptive threshold is chosen for each slice based on histogram analysis of each value.

For the CT abdominal image, a window is fixed by removing the last 30 rows and 50 columns from the right since this area usually does not contain liver region. Then, histogram is drawn and analyzed. The intensities representing background (dark) and bone values (brightest) are removed by making pixel counts to zero. Normally, liver lies in between 100 and 225 intensities range. Since liver area is large compared to other adjacent organs and has constant intensity throughout, the highest pitch corresponds to the liver area. Hence an intensity range with highest count pixels plus certain margin to accommodate any variance in the liver region pixels is adaptively

obtained for each slice. This range represents the liver region pixels.

The pixels in the adaptive threshold range of intensity are extracted. The output looks like scattered sand. It is converted to an object with real area using morphological closing and opening[11]. The liver is extracted along with the fragments of other organs located near to it and with intensity same as that of liver. Since these fragments can affect accurate diagnosis, they can be removed based on area. The area of the liver is large when compared with the fragments of other organs. After removing the fragments, the image obtained is complemented and multiplied with the original image to get the segmented liver in the CT abdominal image.

3.2 Biorthogonal wavelet-based statistical texture feature extraction

From the lowest level of pixel representations, one can gather useful information through a process called feature extraction. In this work, the original image I is represented by a set of sub images at several scales after biorthogonal wavelet transform: $\{ L_d, D_{ni} \}_{i=1,2,3,n=1...d}$ is a multiscale representation of depth d and scale n of the image I. Since each wavelet coefficient D_{ni}(bi,bj) R and the co occurrence matrix or SGLDM is defined for an image with a countable number of gray levels, the co occurrence matrix $C_{ni}{}^{d\theta}$can be defined for each detail image. The element (j, k) of the co occurrence matrix $C_{ni}{}^{d\theta}$is defined as the joint probability that a wavelet coefficient D_{ni} = j co occurs with a coefficient D_{ni} = k on a distance d in direction θ. Usually small values for d are used since most relevant correlation between pixels exists on small distance. Hence, from these three detail images three SGLDM or co occurrence matrixes $C_{11}{}^{d\theta}$, $C_{12}{}^{d\theta}$ and $C_{13}{}^{d\theta}$ are constructed with 1 for d and 0, 45, 90 and 135 degrees for θ and averaged. Then second order statistical features[10] are extracted in horizontal, vertical and diagonal directions (total of 42 features). The feature values are normalized by subtracting minimum value and dividing by maximum value minus minimum value. Maximum and minimum values are calculated based on the training data set. In the test data set, if the feature value is less than minimum value, it is set to minimum value. If the feature value is greater than maximum value, it is set to maximum value. Then values are normalized and are optimized by feature selection algorithm.

3.3 Feature selection

The feature selection problem involves the selection of a subset of 'd' features from a total of 'D' features, based on a given optimization criterion. The D features are denoted uniquely by distinct numbers from 1 to D, so that the total set of D features can be written as S = { 1, 2, ..., D }. X denotes the subset of selected features and Y denotes the set of remaining features. So, S = X U Y at any time. J(X) denotes a function evaluating the performance of X. J depends on the particular application. Here J(X) denotes the classification performance of liver region as fatty or cirrhosis using the set of features in X. In this work, Sequential Forward Floating Search (SFFS) and Genetic Algorithm (GA) techniques are used.

3.3.1 Sequential forward floating search algorithm:

1. X = Φ;

2. Y = { i $1 \leqslant i \leqslant D$ };
3. k = 0 // initialization
4. while (k < d) {
find the most significant feature y in Y and add to X.
find the least significant feature x in X
while (J(X $_k$- {x}) > J(X $_{k-1}$)) {
X $_{k-1}$=X $_k$- {x};
k – 1;
find the least significant feature x.
}
}

The most and least significant feature is selected based on the classification performance, J(X), of PNN classifier for identifying fatty and cirrhosis liver.

3.3.2 Genetic algorithm

GA_select()
{
Initialize population P;
repeat {
select two parents p1 and p2 from P;
offspring = crossover(p1,p2);
mutation(offspring);
replace(P, offspring);
} until (stopping condition);
}

A binary digit represents a feature, values 1 and 0 meaning selected and removed, respectively. As an example, chromosome 00101000 means that the third and fifth features are selected. That is, the chromosome represents X = {3,5} and Y = { 1,2,4,6,7,8}. The initial population is generated by random function.

Initial population:
for (i = 1 to |P|)
for (each gene g in i^{th} chromosome)
if (random() < d/D) g = 1; else g = 0;

The evaluation is straightforward since a chromosome represents a selected feature subset, X, and the evaluation function is clear. In order to force a feature subset to satisfy the given subset size requirement, the size value, d, is taken as a constraint and a penalty is imposed on chromosomes breaking this constraint. The fitness of a chromosome C is defined as

$$\text{fitness}(C) = J(Xc) - \text{penalty}(Xc), \tag{1}$$

where Xc is the corresponding feature subset of C, and penalty(Xc) = w * (|Xc| - d) with a penalty coefficient w. The chromosome selection for the next generation is done on the basis of fitness. The selection mechanism should ensure that fitter chromosomes have a higher probability survival. So, the design adopts the rank-based roulette-wheel selection scheme. If the mutated chromosome is superior to both parents, it replaces the similar parent. If it is in between the two parents, it

replaces the inferior parent; otherwise, the most inferior chromosome in the population is replaced. The selected feature set based on the test data set is used to train the PNN Classifier for classifying the liver diseases to select the optimum feature set.

3.4 Neural network classifiers

In this work, three classifiers namely Probabilistic Neural Network (PNN), Learning Vector Quantization (LVQ) Neural Network and Back Propagation Neural Network (BPN) are considered for classification of the diseases[8,13,16].

3.5 Classification performance evaluation

The performance of the system is evaluated with the radiologist and the patient's doctor. Also the ROC analysis has done with the used data[6]. If both diagnosis and test are positive, it is called True Positive (TP). The probability of a TP to occur is estimated by counting the true positives in the sample and dividing it by the sample size. If the diagnosis is positive and the test is negative it is called a False Negative (FN). False Positive (FP) and True Negative (TN) are defined similarly. Accuracy is given by equation (2).

$$\text{Accuracy} = (TP + TN)/(TP + TN + FN + FP) \tag{2}$$

The values described are used to calculate different measurements of the quality of the test. The first one is sensitivity, SE, which is the probability of having a positive test among the patients who have a positive diagnosis.

$$SE = TP/(TP + FN) \tag{3}$$

Specificity, SP, is the probability of having a negative test among the patient who have a negative diagnosis.

$$SP = TN/(FP + TN) \tag{4}$$

Two other measurements that can be used are the positive predicting value (PPV) and negative predicting value (NPV).

$$PPV = TP/(TP + FP) \tag{5}$$

$$NPV = TN/(TN + FN) \tag{6}$$

The ROC curve has the sensitivity plotted vertically and reversed scale of the specificity on the horizontal axis. The curve gives a picture of the performance of the system.

Also the classification accuracy is evaluated by k-fold cross validation method. In this method, the initial data are randomly partitioned into k mutually exclusive subsets or "folds" S1, S2,..., Sk each of approximately equal size. Training and testing is performed k times. In iteration i, the subset Si is reserved as the test set, and the remaining subsets are collectively used to train the classifier. That is, the classifier of the first iteration is trained on subsets S2,...,Sk and tested on S1; the classifier of the second iteration is trained on subsets S1, S3, ..., Sk and tested on S2 and so on. The accuracy estimate is the overall number of correct classifications from the k iterations, divided by the total number of samples in the initial data. In

stratified cross validation, the folds are stratified so that the class distribution of the samples in each fold is approximately the same as that in the initial data.

4 Implementation and Results

The CT abdominal images were collected from 100 fatty liver patients and 100 cirrhotic liver patients. The CT abdominal image collected from a patient have approximately 20 slices. The slices which are clearly focusing the liver were selected from the available slices of a CT abdominal image. They were in DICOM format. The slices were converted to BMP image which is an acceptable format for medical image processing and is given in Fig.1(a). The liver was extracted using the described methodology (Fig.1(b) – Fig.1(g)) from the image (slice).

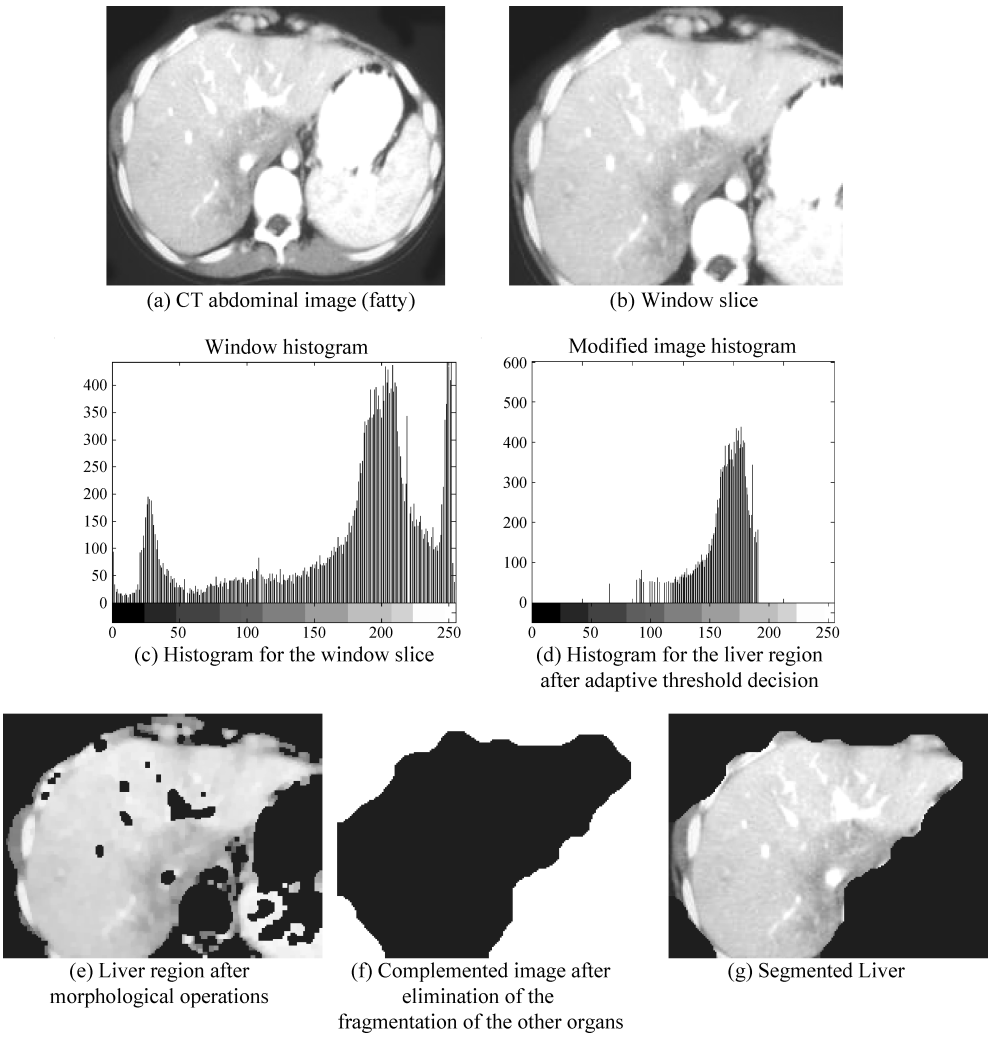

Figure 1. Liver extraction from CT abdominal image

The liver area extraction was carried out within a second successfully based on the above method. The method was tested with 200 slices. A radiologist evaluated

the results. For most of the slices, the liver area was completely extracted, although there were some erroneous cases where other organs adjacent to the liver were also extracted. This is because of adding certain intensities to the middle intensity of the liver region while fixing adaptive threshold. However, most of the cases did not influence much on the recognition because entire liver volume affected by diffused liver diseases is contributing for recognition. The segmentation method is simple and accurate in extracting the liver boundary in most of the slices because of the morphological operations, preserving the shape of the liver. Hence the liver boundary is correctly captured. Adaptive threshold decision solves the problem of varying intensity for patient and CT machine parameters. Also, it is easy to implement compared to the methods discussed by other researchers. The results are compared with the existing results. Most of the images are noise free. If the image contains noise because of the protocol settings, then preprocessing is done to remove noise by applying median filtering technique.

The 42 features for the distance 1 pixel averaging over the angles 0, 45, 90 and 135 degree were extracted as explained in the methodology. Feature selection algorithms SFFS and GA are used to optimize the feature set. Based on the experiments conducted with the available data, SFFS is taking less time and perform the same sequence of operations and always produce the same results. On the other hand, GA executes a different sequence of operations from one to another, and produces a different solution on each occasion. If more CPU time is allowed, GA can produce better solutions. A simple way of giving more time to a GA is to increase the generation number or the population size. The parameter set for the experiments are as follows: Population size 20; Cross over probability 1.0, Mutation rate 0.1, penalty coefficients 0.5 and Stopping condition 20 generations. Since these algorithms repeatedly add and remove features, it is possible that the same subsets are reevaluated. By book keeping the already evaluated subsets and their performance data, we can avoid duplicate computations and speed up the algorithms.

Since the classification accuracy of 95% is obtained with the features Contrast, Entropy, Angular Second Moment and Homogeneity extracted from three detail of images (12 features) and are giving optimal performance in this application domain, the cost of classifier is reduced. Also, the biorthogonal wavelet transform for the depth n = 2 is applied and features are analyzed. There is no improvement in the classification performance other than increase in computations.

Neural network classifiers performance were analyzed based on the experiments with training set of 40 patients (subjects) slices and testing set of 35 patients (subjects) slices in each category. Training and testing data set are disjoint. For designing the classifier, the training set contains 40 fatty liver and 40 cirrhotic liver slices and testing set contains 35 fatty liver and 35 cirrhotic liver slices are considered. The PNN structure designed has 12 neurons in the input units for giving 12 extracted features as inputs, 80 hidden neurons in the pattern units as training set contains 80 feature vectors and 2 neurons in the summation unit for the 2 classes of fatty and cirrhotic liver. The input layer of LVQ has 12 input neurons for giving the extracted features and the output layer has 2 neurons as the number of classes to be identified as 2, fatty and cirrhotic liver with learning rate as 0.01, number of hidden neurons as 64 and number of epochs as 150 for the available data. Single hidden layered BPN

is not converging for the input patterns. This may be due to complexity of input feature vectors or insufficient representation of samples in the training data. Hence two hidden layered neural network architecture is used. The 12 features are given to the input layer neurons. The first hidden layer consists of 25 neurons (12 * 2 + 1) and the second hidden layer consists of 12 neurons. The output layer has 1 neuron to indicate whether the input pattern is a fatty or a cirrhosis liver. The learning rate for input and hidden layer are 0.4, moment is 0.2 and the error allowed is 0.01. Binary sigmoid function is used. After successful training with 400 epochs satisfactory results are obtained. Performance measures for 100 slices obtained from 50 fatty liver patients and 50 cirrhotic liver patients excluding training set patients are tabulated in Table 1. To justify the choice of wavelet domain, for the same data set, without applying biorthogonal wavelet transform, in the gray level domain, the 4 features are extracted and the performance of the neural networks are tabulated also in Table 1.

Table 1. Classification performance for fatty and cirrhosis liver for 100 samples (50 fatty liver patients and 50 cirrhosis liver patients)

Parameter	Wavelet domain			Gray level domain		
	PNN	LVQ	BPN	PNN	LVQ	BPN
TP	48	47	42	46	43	35
TN	47	46	38	44	42	27
FP	3	4	12	6	8	23
FN	2	3	8	4	7	15
Accuracy in %	95	93	80	90	85	62
Sensitivity in %	96	94	84	92	86	70
Specificity in %	94	92	76	88	84	54
PPV	94	92	77.7	88.5	84.3	60.3
NPV	96	94	82.6	91.7	85.7	64.3

From Table 1, it is clear that PNN neural network outperforms LVQ and BPN in accuracy ie. recognition rate. Also time taken for constructing PNN is less since there are no iterative steps while training. Also performance of classifiers in wavelet domain is better than in gray level domain. In terms of memory requirements, PNN needs more memory compared to other classifiers. But nowadays memory cost is low. Hence PNN is a better classifier compared to LVQ and BPN classifiers based on speed and recognition rate.

For evaluating the performance of the system, ROC analysis is done using PNN classifier. The data set divided randomly into 5 groups of 100 slices with 50 fatty and 50 cirrhotic liver cases. The experiment is repeated for each group. Sensitivity and specificity values are recorded for each group and ROC curve is drawn (Fig.2) and analyzed.

Depending on the training set, each group will have a different threshold value for determining true positive and true negative cases. As a result, there will be a trade off between sensitivity and specificity value. Optimum pair of sensitivity and specificity gives a good design. Also, the curve gives an overall performance of the system as, whether the classifier is good, bad or worst. Since the curve follows the left hand border and then top border, the classifier is a good classifier. Hence PNN is chosen as a good classifier in this application domain for classifying fatty and cirrhosis liver.

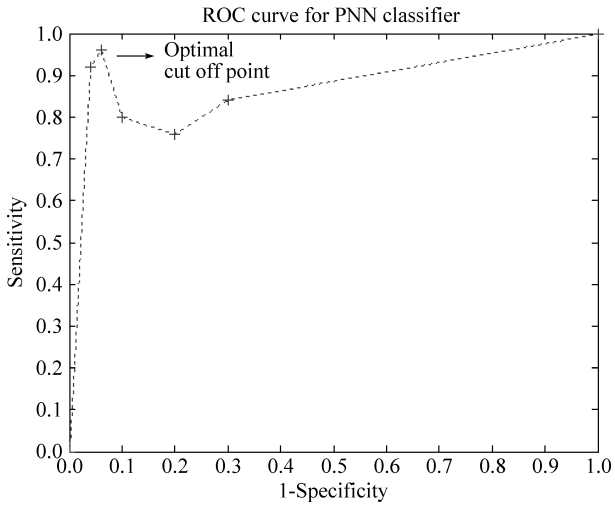

Figure 2. ROC analysis curve for PNN classifier

For evaluating the classification accuracy, 10 fold cross validation is done on the data set collected from 200 patients (100 fatty and 100 cirrhotic patients). The patients are divided into 10 sets each consisting of 10 fatty patients and 10 cirrhotic patients. Then 9 sets are used for training and 1 set is used for testing. Hence 10 iterations are done. For the three iterations 2 patients, another two iterations 1 patient are wrongly classified. For the remaining 5 iterations all are correctly classified. Hence cross validation accuracy obtained is 192 / 200 which is 96%. Results show that, if the number of representative samples is increased, we get good classification accuracy for hold out method and 10 fold cross validation method. Hence PNN can be used as a classifier in this application domain.

5 Conclusion

The segmentation method is simple and accurate in extracting the liver boundary in most of the slices because of the morphological operations preserving the shape of the liver. Adaptive threshold solves the problem of varying intensity for patient and CT machine parameters. Results show that, biorthogonal wavelet based statistical features were yielding better results compared to the statistical features extracted directly from image without applying wavelet transform. This justifies the choice of using wavelet transform. The recognition rate of the PNN classifier for classifying fatty and cirrhosis liver images using CT images is 95% for holdout method. The sensitivity is 96% and specificity is 94%. Using 10 fold cross validation method, 96% accuracy is obtained. Hence it is concluded that the neural networks supported by conventional image processing operations can be effectively used for liver disease diagnosis.

Use of larger databases is expected to improve the system robustness and ensure the repeatability of the resulted performance. The findings of this work suggests that, a much easier hardware implementation of tissue analysis function can be provided in image acquisition machines like CT scanner in the future. The proposed system can be extended for other types of liver diseases like cysts, ascites and steotosis and also for other types of medical images like MRI.

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